The Cost of Wind Power Forecast Errors in the Belgian Power System

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April 14, 2014

Abstract

Driven by growing concerns over the impact of greenhouse gas emissions on climate change, electricity generation from renewable energy sources (RES) has risen considerably over the last decade. Due to their location-specific, variable and limitedly predictable character, they affect the power system in terms of generation and grid adequacy, as well as the need of short term balancing services. In this paper, we will focus on the cost associated with balancing – i.e. maintaining the balance between supply and demand on the short term – resulting from a specific source of uncertainty, namely the error on wind power forecasts. We study the impact of this forecast error on the operational power system costs and carbon emissions in the Belgian power system. Employing a state-of-the-art stochastic modeling framework, we were able to estimate a lower bound on the operational impact of wind power forecast errors. Compared to the literature, this approach is richer in the detail it entails in modeling this uncertainty. Results show that the lower bound on balancing costs varies between 4.3 and 6.7 Euro per MWh of wind energy for wind power penetrations between 5% and 30% of the annual energy demand. If one excludes the cost of a reduced reliability, this balancing cost becomes relatively constant, ranging from 3.6 to 4 Euro per MWh of wind energy. This is the result of the fact that the same units, with similar operational costs, are used to mitigate wind power forecast errors. Carbon emissions are shown to rise 7.4 to 12.7% at a 30% wind energy penetration compared to the case where no uncertainty exists on the wind power forecast. Comparison with a deterministic optimization, considering a conservative reserve requirement, reveals that sub-optimal scheduling of reserves can lead to strongly increased balancing costs, up to 8.3 Euro per MWh wind energy. These results show that utilities, power system operators and policy makers should aim to improve forecast methodologies and employ state-of-the-art reserve sizing methods to mitigate the resulting balancing costs of the remaining uncertainty. Results furthermore indicate that the gas-fired units which are used to provide the needed balancing services will have less and less full load operating hours as the share of wind energy increases. Future work may investigate whether this is sufficient for operators to recover their fixed costs, in order to assess the need for capacity mechanisms. A solution to this weakness may be to include investments and disinvestments in the model. In addition, the obtained balancing costs should be compared to and validated against market data, such as imbalance volumes and prices, as well as (activated) reserve volumes.

1 Introduction

Present-day and future power systems are characterized by increasing shares of intermittent generation from renewable energy sources (RES). Especially in Europe, wind and solar power capacities have steadily risen over the last years. The total wind power capacity in Europe now well exceeds 115 GW [2], while in 2013 alone over 10 GW of solar power was connected to the grid [3]. The integration of such a massive amount of RES in the power system leads to certain so-called *integration costs*. These costs are the result of three specific characteristics of power generation from RES [4]. First, they are *location specific*, meaning that generation occurs where the wind blows or the sun shines, which not necessarily coincides with the location of the demand. Second, generation from RES is *variable*, meaning that their output fluctuates in time. As a result, other dispatchable units must be available to cover the demand when the output of RES is too low (or absent). Moreover, the demand profile faces by conventional power plants becomes more variable, leading to increased cycling of these units [5]. Last, their output is *only predictable to a certain extent*, leading to the need of back-up capacity. As a result, power systems are affected on three fronts [6]:

- *adequacy* – maintaining the power system balance on the long term;
- *balancing* requirements - related to the short term system balance of the system and reserves;
- *grid* – the increased need for transmission, voltage stability measures, ... due to the intermittent and location-specific character of RES.

In addition, one should not forego so-called *profile costs* [4], which can be related to the variability of the generation from RES.

In this paper, we will focus on the balancing cost resulting from a specific source of uncertainty, namely the error on wind power forecasts (WPFE), and the impact of this forecast error on the operational power system costs and carbon emissions[1]. The focus will be on short-term balancing, but not on the shortest time scales (seconds to minutes). We will estimate the balancing cost from a system perspective, which may be different from the market cost, depending on the market structure. We will focus on the Belgian power system, in which at the moment over 1.5 GW of wind capacity is connected to the grid. To illustrate the challenges that this imposes on the system, the forecasted and measured wind power in the Belgian power system between February, 10^{th} and February, 18^{th} 2014 is shown in Fig. 1. Forecast errors of over 500 MW – the size of a combined cycle gas turbine – and steep ramps are not uncommon, illustrating the importance of accurate forecasts and adequate short-term balancing mechanisms (e.g. reserves). The relationship between wind forecasts and unit commitment has become of such importance that some modelers go so far as to include a state-of-the-art numerical weather prediction model within the same closed-loop optimization as a unit commitment and economic dispatch [8].

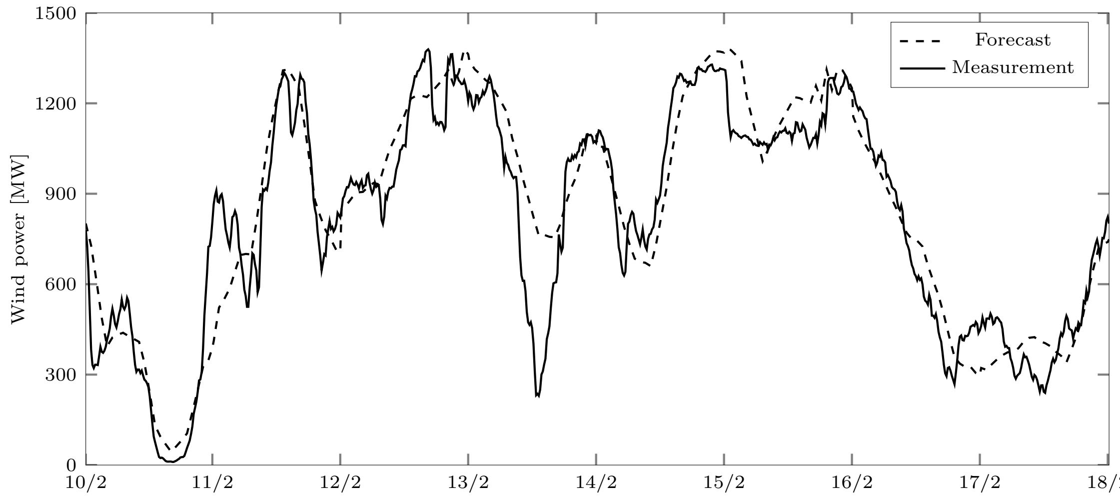


Figure 1: The large forecast errors oberved in the Belgian power system illustrate the need for adequate short-term balancing mechanisms to maintain the system balance. The forecasted and measured wind power in the Belgian power system between February, 10^{th} and February, 18^{th} 2014. Source: Elia NV [9].

[1] We will expand the work presented at the 2nd BAEE research workshop (Benelux Association for Energy Economics) [7].

To assess the balancing costs that result from various penetration levels of wind power, we develop a stochastic modeling framework, based on a detailed analysis of the underlying stochastic character of the wind power forecast error [10], a scenario generation technique to represent that stochastic character in discrete set of scenarios [11] and a stochastic unit commitment model [12–15]. Such a unit commitment model mimics a day-ahead electricity market in which perfect competition exists. Power plants are scheduled and dispatched in order to meet the demand for power at minimum operational costs (fuel costs, emission costs, start-up and cycling costs), calculated as a weighted average over all scenarios. In a stochastic unit commitment model, reserve calculations are internalized through the consideration of a set of representative scenarios, which allows for optimal planning of the required flexibility [16]. The operational costs, obtained from this stochastic model, will be compared to a deterministic variant in which the system operator has perfect foresight on the available wind power. If one considers sufficient scenarios in the stochastic model, this model returns the best possible decision a system operator can make given the uncertainty. This will yield a lower bound on the balancing costs due to the integration of wind power. A (possible) upper bound of the balancing cost estimate is given by a deterministic unit commitment model, in which upward reserve constraints inspired a report released by Elia NV, the Belgian transmission system operator, are enforced [1]. As discussed below, this is a very conservative approach, resulting in a high reliability, but considerably higher balancing costs. We will not consider investments nor disinvestments in generation capacity. As such, the resulting balancing costs need to be interpreted as so-called 'short-term' balancing costs [4].

The added value of this work lies in the detail the proposed methodology contains in terms of the modeling the uncertainty. E.g. the consideration of cycling costs, in addition to fuel, carbon and start-up costs and the full stochastic simulation framework [11, 12], which will allow us to determine a lower bound on the cost of the limited predictability of wind power.

Results indicate that the lower bound on balancing costs varies between 4.3 and 6.7 Euro per MWh of wind energy for wind power penetrations between 5% and 30% of the annual energy demand. If one excludes the cost of a reduced reliability, the balancing cost becomes relatively constant, ranging from 3.6 to 4 Euro per MWh of wind energy. This is the result of the fact that the same units, with similar operational costs, are used to balance wind power, for these penetration rates. With the stochastic unit commitment model, carbon emissions are shown to rise up to 7.4% compared to the case where no uncertainty exists on the wind power forecast. Comparison with a deterministic optimization, considering a reserve requirement inspired by Elia [1], the Belgian TSO, reveals that sub-optimal scheduling of reserves can lead to strongly increased balancing costs, up to 8.3 Euro per MWh. This shows that power system operators, utilities and policy makers jointly should strive to improve forecasts on renewables, as balancing costs are non-negligible, even at low wind power penetrations. Furthermore, state-of-the-art operational modeling techniques, such as stochastic unit commitment models, should be employed to estimate the required reserves needed to cover the remaining uncertainty, in order to minimize the resulting balancing costs.

The remainder of the paper is organized as follows. First, a brief literature review on the impact of wind power on balancing costs will be presented. Although methods and approaches in literature are divers, results consistently indicate a balancing cost of 1 to 4 Euros per MWh wind energy in thermal-dominated power systems. Second, the proposed methodology is introduced. After a description of the methodology followed in the present paper, Section 4 covers the model, data and assumptions. Results are discussed in the subsequent section, before moving to a conclusion in Section 6.

2 Literature review: the impact of wind power on balancing costs

Numerous academic articles, reports and meta-studies on the integration costs of renewables – and wind power in particular – have appeared over the last decade. Some researches have tried to summarize the results of these studies by calculating the additional costs for balancing wind power. The most recent overviews have been composed by Holtinnen et al. [6, 17] and Hirth et al. [18]. Although the regions studied and the methodologies used are quite different, most studies conclude that balancing costs for wind energy vary between 1 and 4 Euros per MWh of wind energy for thermal-dominated systems and are less than 1 Euro per MWh of wind energy for hydro-dominated systems (Fig. 2). In the latter case, balancing costs drop considerably as hydro units can provide balancing services at almost zero-cost. This is contradicted by the recent NEA report 'Nuclear Energy and Renewables', which reported balancing costs up to 5.3 Euro per MWh wind energy in Finland [19]. Balancing costs in most cases slightly increase with the wind power penetration. Hirth et al. [18] report balancing costs up to 6 Euros per MWh and some outliers up to 12 Euro per MWh. The latter was only reported for very low wind power penetrations and were obtained from market data analyses of power systems with punitive mark-ups on the imbalance prices.

In general, one can distinguish between two types of studies that estimate the cost of additional balancing services to overcome wind power forecast errors. A first group of studies uses *market data*, i.e. observed imbalances, imbalance prices and activated reserve volumes. Such evaluations are limited to the historical conditions (e.g. low penetrations, market design) and many imbalance markets do not reflect the marginal cost of providing those balancing services [4]. Moreover, market failures are not uncommon and forecasts may be biased due to the market design or the forecast methodology. Alternatively, researchers use *unit commitment and dispatch models* to investigate the impact of imperfect forecast on power system operations, reliability and system costs. These models have their obvious shortcomings, such as the accuracy of the model in representing a real-life power system, sensitivity to data, . . . and some more subtle features that drive the obtained results. First, most models are deterministic in nature (e.g. Delarue et al. [20], Ortega-Vazquez and Kirschen [21], Sioshansi [22], Andrianesis and Liberopoulos [23], NREL [24] and the 'implications of intermittency' study by Pöyry [25]). This means that the resulting generation schedule is optimal for the forecasted wind power injection, given a set of constraints that represent the techno-economic limitations of the power plants available. Uncertainty is tackled by scheduling reserves. The cost of uncertainty is then calculated by comparing the cost of this solution (including the reserves) to a solution in which no reserves were required and/or a dispatch of the resulting unit commitment over a (large) number of possible realizations of wind power. However, the quality of the reserve requirements (and the assumption on the value of load that must be shed when these reserves are inadequate) fully determines the outcome of the model. Moreover, very few studies execute multiple dispatches – considering different wind power scenarios – for each generation schedule to evaluate the cost of activating the reserves. If this step is not considered, one only obtains an estimate for the so-called *reservation cost* of the additional reserves. By evaluating the generation schedule for multiple wind power scenarios, a statistically relevant estimate of the *activation cost* of those reserves can be obtained. Second, these models typically only discuss the direct costs of imperfect forecasts. Indirect costs, such as cycling costs [26], are not taken into account [24]. These indirect costs can however be significant [5][2]. Last, these studies often fail to differentiate between costs due to the variability and the limited predictability of RES.

As an alternative to the first shortcoming of unit commitment models, stochastic variants are proposed[3]. These models differ from the deterministic variant in the way they tackle the uncertainty in the system (see Bruninx et al. [12, 16] and Section 4). The uncertainty is represented via a discrete set of scenarios – i.e. possible realizations of the uncertain variable that occur with a certain probability. The generation schedule is then optimized to minimize the expected operational cost – i.e. a probability weighted average of the operational cost over the set of scenarios. The unit commitment status is common to all scenarios, which then abolishes the need for reserves requirements. In effect, the reserve calculation is internalized: the model will schedule the needed capacity to maintain the system balance in all considered scenarios at the lowest operational cost. In theory, one can determine a lower bound

[2]In [5], cycling costs due the increased variability with rising shares of renewables are assessed. In this paper however, we are investigating the effect of imperfect forecast on these cycling costs.

[3]Note that the definition of *stochastic unit commitment models* in this paper is different from the one used by Hirth et al. [18]. The models that are listed in [18] in the paragraph on stochastic unit commitment models (page 12) are in fact all deterministic, expect the work by Tuohy et al. [14] and Gowrisankaran et al. [27].

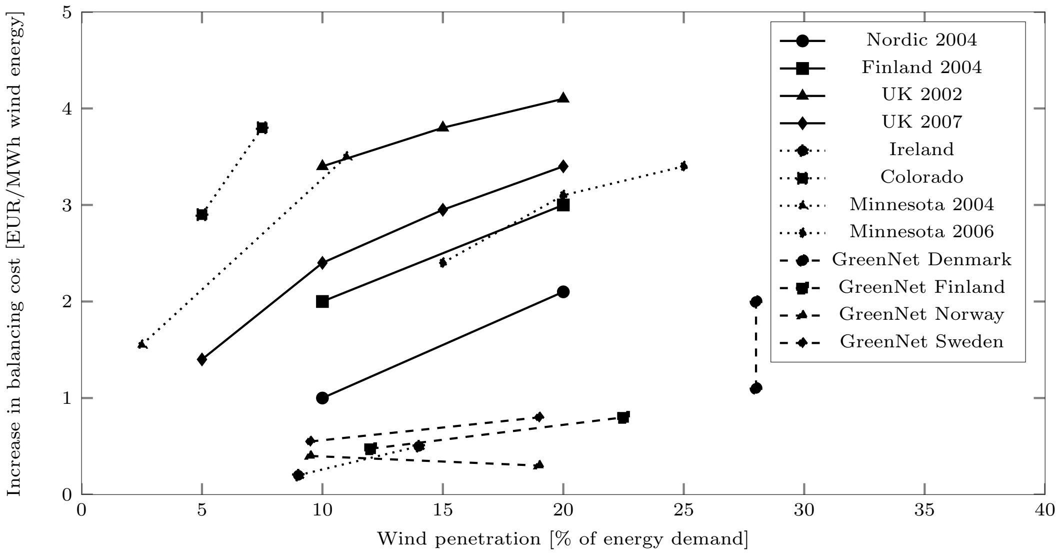


Figure 2: Balancing costs are estimated between 1 and 4 Euros per MWh of wind energy for systems dominated by thermal units and less than 1 Euro per MWh wind energy for hydro-dominated systems. Selected data from Holtinnen et al. [6, 17].

on balancing (and cycling costs) due to forecast errors, if one uses sufficient scenarios to capture the stochastic behavior of wind power (forecast errors) to reach the stable solution of the stochastic problem.

Few researchers have attempted the estimate of the (lower bound on the) cost of imbalances as a result from wind power forecast errors via a stochastic unit commitment model. Tuohy et al. [14] study the Irish system with an assumed wind power penetration of 34.2% of the gross demand. They use an improved version of the well-known WILMAR model. Although not explicitly mentioned, an additional balancing cost of 3 Euro per MWh wind can be calculated from the reported results. However, the model used still carries reserve constraints, which may lead to suboptimal results compared to a pure stochastic unit commitment model: if the model carried sufficient scenarios to yield a stable solution [11, 12, 28], the reserve constraints do not have any added value. At best, these constraints leave the stable solution unaffected. If these reserve constraints are however too binding, they may make it impossible to reach the optimal solution of the 'true' stochastic programming problem. Moreover, the calculated balancing cost excludes the cost of load shedding. Cylcing costs are not taken into account. Sturt and Strbac [13] investigate the British power system with a wind penetration of 35%. The cost of uncertainty varies between 4.7 and 6.8 Pound Sterling per MWh of available wind energy. Although the reported start-ups of the considered fleet of power plants changes drastically under uncertainty, this is not reflected in increased cycling costs.

Compared to the current literature, this paper will provide added value on two fronts. First, cycling costs are considered, in addition to fuel, carbon and start-up costs, in the analysis. This will allow to allocate the cost increase as a consequence of unpredictability to each of these costs. Second, we will employ an detailed and verified stochastic simulation framework [11, 12], which will allow us to determine a lower bound on the cost of the limited predictability of wind power. In addition, we will compare these results to a deterministic scheduling policy, which will be constrained to conservative reserve requirements inspired by work of the Belgian TSO, Elia NV [1].

3 Methodology

The proposed methodology consists of four main steps. First, the distribution of the wind power forecast error is analyzed and reduced to a conditional probability distribution of a certain error occurring given the forecast at that time step. Second, this distribution will be used to generate a set of scenarios for each forecast that captures all relevant statistical properties of that forecast errors. Third, two unit commitments model are solved for each day: a deterministic model with reserve constraints inspired by Elia [1] and a stochastic model. Last, the resulting solution – i.e. the resulting unit commitment – is analyzed in a Monte-Carlo setting. For a large set of scenarios, generated in step 2, a dispatch is executed for each unit commitment schedule in order to obtain a proxy for the expected performance of the model. In parallel, a deterministic model without any uncertainty on the wind power forecast and without any reserve requirements is solved for each scenario, yielding the benchmark for our analysis. Step 1 is only executed once, while step 2 to 4 are needed for each day that we would like to study. A visual overview of this methodology is given in Fig. 3.

Step 1: Statistical analysis As a first step, we developed a statistical description of the WPFE [10]. In this paper, we will not go into detail on the methodology used, but the obtained distributions are essential in terms of input data to for the rest of the methodology. In [10], we show that the WPFE is heavy-tailed and skewed, dependent on the forecast. This behavior cannot be captured through – although it is often assumed – a Gaussian distribtion. As an alternative, we proposed the Lévy alpha-stable distribution. For the remainder of the discussion, it is sufficient to understand that we obtained a marginal probability distribution of the WPFE of the error given the forecast that captures the aforementioned characteristics.

Step 2: Scenarios In the ideal case, one would optimize the unit commitment schedule considering the full, continuous description of the WPFE. Computational limitations however do not allow this. Therefore modelers try to design sets of scenarios – i.e. discrete realizations of the stochastic variable – that capture the WPFE distribution. In this paper, we employ a scenario generation technique based on Pinson et al. [29]. In [11], we evaluate the scenarios in terms of the probability density function of the WPFE (variability) and for a number of critical events, based on the method described in [30]. In the present paper, we will not discuss the scenario generation method in detail – it suffices to understand that a set of 100 scenarios allows us to capture the distribution of the forecast error, the variability of the error and a large number of assumed-to-be critical events [11].

However, solving a stochastic unit commitment model which considers 100 scenarios is computationally next to impossible. To avoid intractability, a scenario reduction technique is employed. The aim of this method is to select a set of scenarios with a predefined, low cardinality, that will yield a stable solution of the stochastic model. The proposed algorithm is a modified *forward selection* scenario reduction technique, in which a probability distance functional between the original and reduced set of scenarios is minimized [31, 32]. A full description can be found in Bruninx et al. [11].

Step 3: Unit commitment A unit commitment model mimicks a day-ahead electricity market in which perfect competition exists. Power plants are scheduled and dispatched in order to meet the demand for power at minimum operational costs (fuel costs, emission costs, start-up costs, ramping costs). In this paper, we employ two unit commitment models. First, a deterministic model considering a reserve constraint inspired by Elia [1] is solved. This model carries reserve constraints based on the reserve capacity based on the '2018 reserve study' [1]. Elia NV provides an estimate of the additional reserve capacity needed by 2018 to cope with an increasing penetration of intermittent renewables in the Belgian power systems. The provided figures are linearly extrapolated to higher wind power penetrations. This conservative approach will yield a high reliability, but at a relatively high balancing cost. Second, a stochastic unit commitment model considering the reduced set of scenarios from step 2 is used to generate an more cost-optimal unit commitment schedule.

Step 4: Dispatch To evaluate the performance of the day-ahead stochastic unit commitment, we look towards the so-called second stage optimization results (dispatch), while fixing the first stage optimization variables (unit commitment). For each scenario, a dispatch is performed given the (fixed) day-ahead unit commitment of all power plants. This dispatch is performed over a statistically significant set of scenarios to get a proxy of the expected performance – in terms of reliability and system cost – of the calculated unit commitment. This dispatch is executed with a deterministic unit commitment model, without any

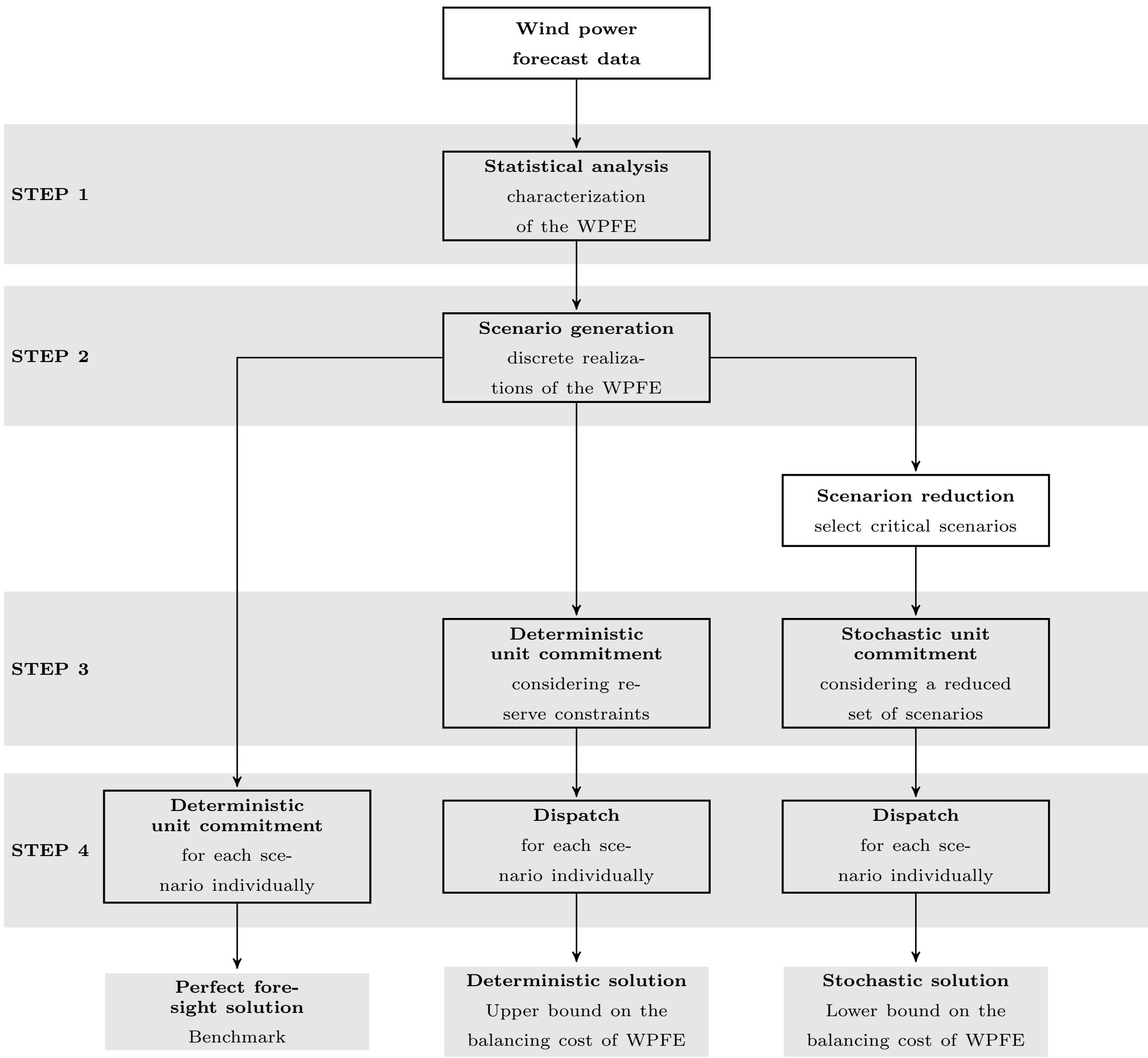


Figure 3: Visual representation of the methodology employed in this paper to obtain estimates for the balancing cost of wind power.

reserve constraints, in which the unit commitment was fixed to the solution of the two unit commitment models described above. As the deterministic unit commitment model with a reserve constraint is the most conservative way of dealing with the uncertainty on wind power forecasts, the expected cost of this operational strategy, calculated as the weighted average of the objective value of the dispatches in every scenario, will provide an ‘upper’ bound on the cost of wind power forecast errors. The state-of-the-art stochastic model takes into account very specific and detailed information on the wind power forecast error. These models are currently not yet used in practice for the calculation of the required reserve levels. The reserve calculations are internalized through the consideration of a set of significant scenarios, which allows for optimal planning of the available flexibility. As such, it will yield a lower bound on the cost of wind power forecast errors.

In parallel, we will use a deterministic model without any reserve requirements or uncertainty as a benchmark. For each of the scenarios, this model will yield the *perfect foresight* solution – no uncertainty on the wind power forecast exists in these results. Comparison of the *deterministic solution* and the *stochastic solution* with the perfect foresight solutions will allow to determine a range for the additional balancing costs on system level with increasing wind power penetration levels.

4 Model, data & assumptions

In this section, a stochastic unit commitment model is formulated using Mixed Integer Linear Programming. This model is based on the deterministic unit commitment model as described in [33]. The stochastic model is inspired by Conejo et al. [34, 35]. The minimum up time and down time constraints are formulated as in Rajan et al. [36]. A full description of the model can be found in [12]. The model is implemented in GAMS 24.1 and MATLAB® 2011b, using the MATLAB®–GAMS coupling as described by Ferris [37]. CPLEX 12.5 is used as solver. Simulations were run on the high performance computing cluster of KU Leuven, using quad-core 2.8 Ghz processors with 24 GB of RAM.

4.1 A stochastic unit commitment model

In all stochastic unit commitment models, one tries to find a unit commitment as such that a feasible dispatch is possible for all possible realizations (scenarios) of an uncertain variable, in this case wind power (see Figure 4). A feasible dispatch here means that the demand for electricity in each time step is met in all of the considered WPFE scenarios, while respecting all techno-economic constraints of the power plants. In this simple model, the so-called *here-and-now* or *first stage* variables– i.e. the variable(s) that are optimized independent of the scenarios – are the unit commitment status of the power plants and the pumping or turbining status of the pumped hydro storage. All other optimization variables, such as the output of the power plants, curtailment of RES and the output of the pumped hydro storage, are so-called *wait-and-see* or *second stage* variables – i.e. the variables that take on different values in each scenario.

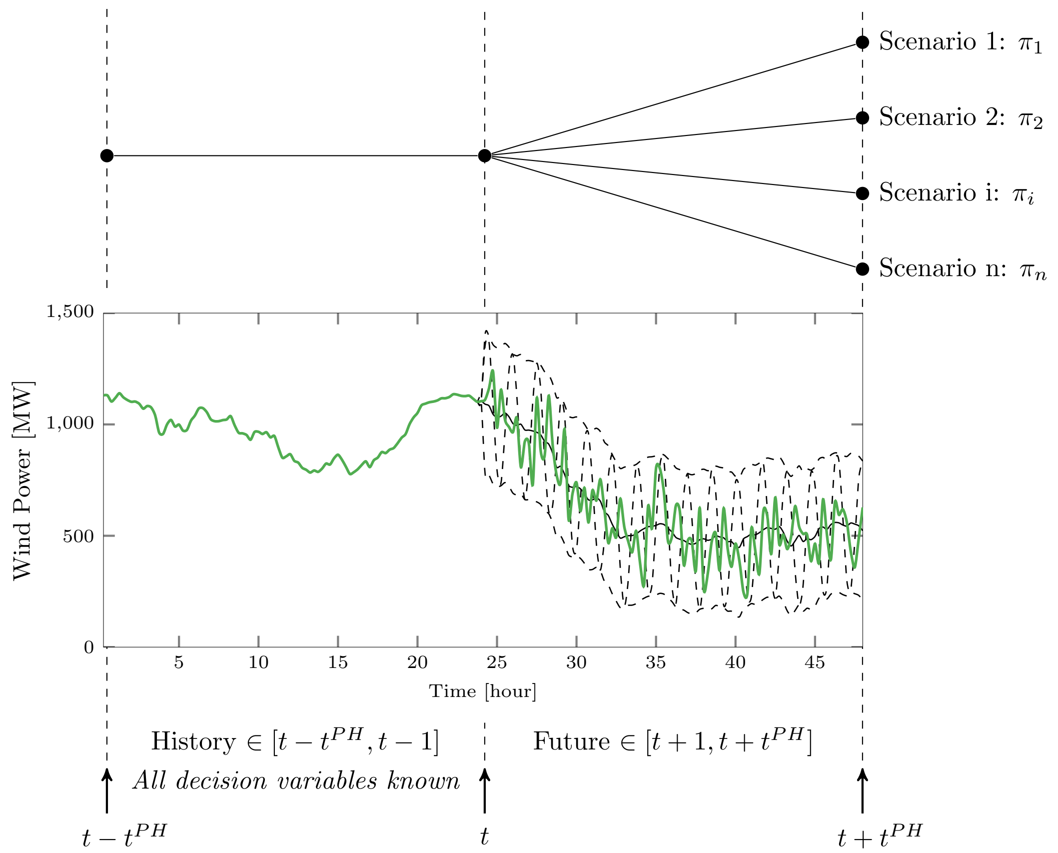


Figure 4: In the this two-stage stochastic unit commitment model the system planner has to decide on the unit commitment at the root node (time step t), taking into account the previous values of the decision variables $[t - t^{PH}, t]$ and the wind power forecast, WPFE scenarios and their probability π_i. The wind power scenarios are indicated in black (WPFE scenarios: dashed, forecast: solid line). The actual wind power is indicated in green. At time step t, this information is not known to the system planner.

The power plants are scheduled and dispatched in such a way that the overall expected cost of generating the demanded electricity over the simulated time period is minimized. This cost $c(g,z)$ consists of fuel costs $FC_{i,j,s}$, start-up costs $SC_{i,j}$, ramping costs $RC_{i,j,s}$ and CO_2-emission costs $CO_2T_{i,j,s}$. The objective function reads

$$min \quad c(g,z) = \sum_i \sum_j SC_{i,j} + \sum_i \sum_j \sum_s prob_s \cdot [TP \cdot (FC_{i,j,s} + CO_2T_{i,j,s}) + RC_{i,j,s}] \tag{1}$$

where I is the set of power plants present in the model (index i) and J is the set of time steps (index j, one time step is one hour). The scenarios, with $prob_s$ the probability of scenario s, are indicated by the index s (set S). TP stands for the temporal resolution used in the optimization. The fuel cost ($FC_{i,j,s}$) is determined by the fuel price, the (part-load) efficiency and the operating point of the power plant via a linear approximation of the quadratic cost curve of each power plant. Similarly, the CO_2 cost $CO_2T_{i,j,s}$ is based on the emissions, the load level and a fixed CO_2 price per ton. For each start-up, a fixed start-up cost is charged, different per power plant and fuel. We have not differentiated between hot and cold start-ups. Last, ramping costs are incured for each change in output of a power plant (except during shut-downs or start-ups), different per power plant and fuel.

In each scenario and at every time step, the demand for electricity must be satisfied by the injection of wind power, the injection from must-run units and the dispatch of conventional power plants or pumped storage units. The so-called market clearing condition reads:

$$\forall j, \forall s: \quad d_j = \sum_i g_{i,j,s} + g_j^{MR} + g_j^F + WPFE_{j,s} - \chi_{j,m,s} + \sum_r \left(\epsilon_r^{PHS} \cdot g_{r,j,s}^{PHS,T} - g_{r,j,s}^{PHS,P} \right) \tag{2}$$

The demand d_j on each time step j is assumed to be known and fixed (parameter of the model). This demand must be met by

- electricity generated from dispatchable power plants $g_{i,j,s}$;
- generation from must run systems with a known output (including electricity generation from RES other than wind) g_j^{MR};
- the forecast of some uncertain electricity generation, in this case wind power, g_j^F, and the wind power forecast error $WPFE_{j,s}$, which can be curtailed ($\chi_{j,s}$);
- the net injection of power from pumped hydro storage plants (index r), calculated as the difference between the injection of power $g_{r,j,s}^{PHS,T}$ and the withdrawal of power $g_{r,j,s}^{PHS,P}$, accounting for the round trip efficiency of the pumped hydro storage ϵ_r^{PHS}.

The dispatchable units are subjected to some techno-economical constraints, different per fuel and technology, such as min. stable operating point, max. operating point, ramping constraints and minimum up and down times. The pumped hydro storage units are subjected to constraints on the storage basin water level and their capacity. This model does not take into account the possibility of adaptations to the unit commitment during the second stage optimization (i.e. the dispatch): the only possible reserves that can be scheduled are spinning reserves. During the unit commitment phase, load curtailment is not allowed. A full description of the model can be found in [12].

The deterministic model is a one-scenario equivalent of the stochastic model: it only considers one scenario, i.e. the forecasted wind power. A demand for upward reserves $dfru_j$[4] is added to the model:

$$\forall j: dfru_j \leq \sum_i \left(P_i^{MAX} \cdot z_{i,j} - g_{i,j} \right) + \sum_m \chi_{j,m} - \sum_i \left(P_i^{MAX} - P_i^{MIN} \right) \cdot (v_{i,j} + w_{i,j+1}) \tag{3}$$

At each time step j, the demand for upward reserves must be met by free online capacity $\sum_i P_i^{MAX} \cdot z_{i,j} - g_{i,j}$, with P_i^{MAX} the maximum output of power plant i, $z_{i,j}$ the binary on-off status of a power plant and $g_{i,j}$ the output of a power plant i. A power plant is not allowed to deliver reserves if it is running at its minimum operating point (P^{MIN}) due to a start-up or shut-down, where binary variables $v_{i,j}$ and $w_{i,j}$ indicate a start-up, resp. a shut-down of power plant i on time step j. If curtailment of RES $\chi_{j,m}$ is scheduled, this is accounted for in the demand for reserves. As wind power is the only source of uncertainty considered in this paper and can only be regulated downward – i.e. curtailment of excess wind power –, it is assumed that all downward reserves are ensured by curtailment. There is

[4] Only valid for power plants with a minimum up time/down time of at least 2 time steps. For power plants with a minimum up or down time of 1 hour, this equation has to be duplicated, once to exclude the provision of reserves by that plant at start-up and once at shut-down [12].

Table 1: Technical characteristics of the power plants in the model [12], based on Elia [9], Schröder et al. [38], ENTSO-E [39] and own calculations.

Technology	Fuel		Costs			Efficiency		Dynamics			
	Fuel	Fuel cost $\left[\frac{\text{EURO}}{\text{MWh}_{\text{prim}}}\right]$	Start-up costs $\left[\frac{\text{EURO}}{\text{MW}}\right]$	Raming cost $\left[\frac{\text{EURO}}{\text{MW}}\right]$	CO_2-content $\left[\frac{\text{tCO}_2}{\text{MWh}_{\text{prim}}}\right]$	Max. efficiency $\eta(P^{\max})$ [%]	Relative efficiency A [−]	$P^{\min}$ [$\%P^{\max}$]	Ramp-up $\left[\frac{\%P^{\max}}{\min}\right]$	Min. up-time [h]	Min. down-time [h]
PWR	UO_2	2	35	-	0	33	-	50	3	8	8
SPP	Coal	12	80	1.8	0.338	35–46	0.08	43	3	6	3
SPP	Gas	25	73	1.4	0.205	40–48	0.08	40	2	4	2
CCGT	Gas	25	45	0.5	0.205	40–58	0.20	35	2	2	1
GT	Gas	25	42.4	0.8	0.205	35–42	0.30	30	6	0.5	0.5
ICE	Oil	35	42.4	0.8	0.281	40–48	0.30	35	10	0.25	0.25

no additional constraint imposed on the downward flexibility of the conventional power plants. Pumped hydro storage is not scheduled to satisfy the demand for reserves, as the availability of the reserves would not be guaranteed. The demand for reserves is constrained to the range of possible WPFE errors and the demand for electricity to avoid excessive scheduling of reserve power.

4.2 Data & assumptions

As we study the Belgian power system, wind power and demand data, as well as the generation system data, are obtained from the Belgian TSO Elia NV. Using 2011-2013 data, the Belgian power system is simulated for the first month of the year, which has a wind penetration very close to the yearly average. Wind power penetration levels, indicating the annual share of electrical energy provided by wind power, ranging from 5% to 30% are studied. Note that the only source of uncertainty considered in this study is the uncertainty on wind power forecasts. Other sources of uncertainty, such as imperfect forecast of the demand or other intermittent RES, as well as forced outages of conventional power plants, are not modeled.

Electrical energy from RES other than wind (7% of annual energy demand) is treated as a demand correction and cannot be curtailed. The demand profile (2011) and wind power data (2012–2013) are obtained from Elia, the Belgian TSO [9]. For sake of simplicity, the transmission grid is not taken into account. Import and exports are not considered. The Belgian conventional generation system, consisting of 71 power plants and combined heat and power plants, has been taken from Elia [9]. The nominal efficiency of the plants is based on the type, the fuel and the age of the power plant. The other technical characteristics of the power plants are based on Schröder et al. [38] and ENTSO-E [39]. A summary can be found in Table 1. Ramp-up and ramp-down constraints are assumed equal. The start-up costs depend on the fuel and size of the power plant. They cover direct and indirect start-up costs [5]. Ramping costs are taken from [5]. The relative efficiency A allows to calculate the efficiency η of the power plant in partial loading conditions (output g, varying between 0 and the maximal output of the plant $P^{\max}$) via the following equation:

$$\eta(g) = \eta(P^{\max}) \cdot \left[1 + A \cdot \ln\left(\frac{g}{P^{\max}}\right)\right] \tag{4}$$

One pumped hydro storage power plant has been included, with a maximum capacity of 1308 MW, a round trip efficiency of 75% and a storage capacity of 3924 MWh. The minimum energy content of the storage facility is set to 10% of the maximal capacity. The CO_2-price is set to 10 $\frac{\text{EURO}}{\text{tCO}_2}$. The value of lost load is set to 10000 $\frac{\text{EURO}}{\text{MWh}}$.

The planning horizon considered in the optimization is 24 hours. The time step in the optimization is 15 minutes. Each optimization takes into account the values of the optimization variables over the previous 24 hours, based on the dispatch taking into account the scenario that represents the measured wind power output on the previous day (see Fig. 4). The dispatch (step 4) is performed for 100 scenarios per day to get a proxy of the expected performance – in terms of reliability and system cost – of the calculated unit commitment. This set of scenarios is a sufficient representation of the uncertainty on the wind power forecast [11].

In the deterministic model, we consider a reserve requirement that is inspired by the report on ancillary services by Elia NV [1]. This reserve calculation as performed by Elia considers all forms of uncertainty in the system. From this, we distilled a linear trend, expressing the increase of reserve requirements with increasing wind power penetration (about 62 MW per per cent of wind energy in the annual energy demand). However, this is only the incremental reserve capacity, which is added to a fixed 'base' of reserve capacity estimated at 1123 MW. At a 5% wind penetration, this yields a reserve capacity of 1433 MW, which is to be compared to an installed wind power capacity of 1.7 GW. To avoid an unreasonably high reserve requirement, the demand for reserves is limited to the forecasted wind power (see above). In effect, this means in the case of a wind power penetration of 5% that the deterministic model requires reserves for the forecasted wind power. As the wind power penetration increases, this reserve requirement diminishes. At a 30% wind energy penetration, about 10 GW of wind capacity is available. The maximum reserve requirement at this penetration is 3 GW. This conservative approach leads to a high reliability (see below), but at an elevated operational (balancing) cost. Lowering this 'base' of reserve capacity could lead to increased load shedding, which would lead to unrepresentative results.

4.3 Validation

As a stochastic unit commitment model has been used, it is important to ascertain the in- and out-of-sample stability of the solutions obtained from the model [11, 12]. Kaut and Wallace [28] argue that *stability* can be tested by solving the stochastic program with several different scenario trees of increasing cardinality, generated by the same method. If the objective value does not change (too much), we can claim in-sample stability. The second requirement for stability is out-of-sample stability. This out-of-sample stability guarantees that the true objective function for the set optimal first-stage decision variables, obtained from solving the stochastic program, does not change (too much) if the cardinality of the scenario tree increases [28]. This can easily be tested by fixing the first stage decision variables – i.e. the unit commitment – to the solution of the SUCM and solving all second stage problems resulting from the original set of scenarios. These stability requirements will set a lower bound on the cardinality of the reduced scenario set. We have performed the stability test for several selected days throughout the year. From these tests, we can conclude that 25 scenarios will suffice to capture the wind power forecast error and yield a stable solution.

The *optimality gap* or *bias* of the proposed scenario generation technique should be small. The optimality gap is the difference between the value of the true objective function at the optimal solutions of the original problem (with a continuous, full description of the stochastic variable) and the approximation of the problem (with a discrete representation of the stochastic variable – i.e. the scenario tree). As calculating this error would require solving the original problem, approximations have been developed. Kaut and Wallace [28] argue that a stochastic upper bound for the bias of the method can be obtained, assuming a stable scenario reduction technique, by comparing the second stage objective function of the stable solution with that obtained with scenario trees of a slightly different cardinality. We performed the test with 10 trees with slightly different cardinality, in this case ranging from 20 to 30 scenarios [12]. Based on this test, the bias is does not exceed 1%, i.e. the optimality gap of the optimization.

5 Results & discussion

In this section, the effect of integrating wind power on the operational cost of generating electricity is discussed. In addition, we discuss CO_2 emissions, reliability and the impact on conventional generation units. Due to the computational cost of the stochastic unit commitment model (approximately 5 hours computation time per day), the first 31 days of the year were analyzed. During this period, the wind power penetration is almost equal to the annual wind power penetration. Although this is expected to result in a good proxy for the annual balancing cost of wind power, further research is needed to confirm this statement.

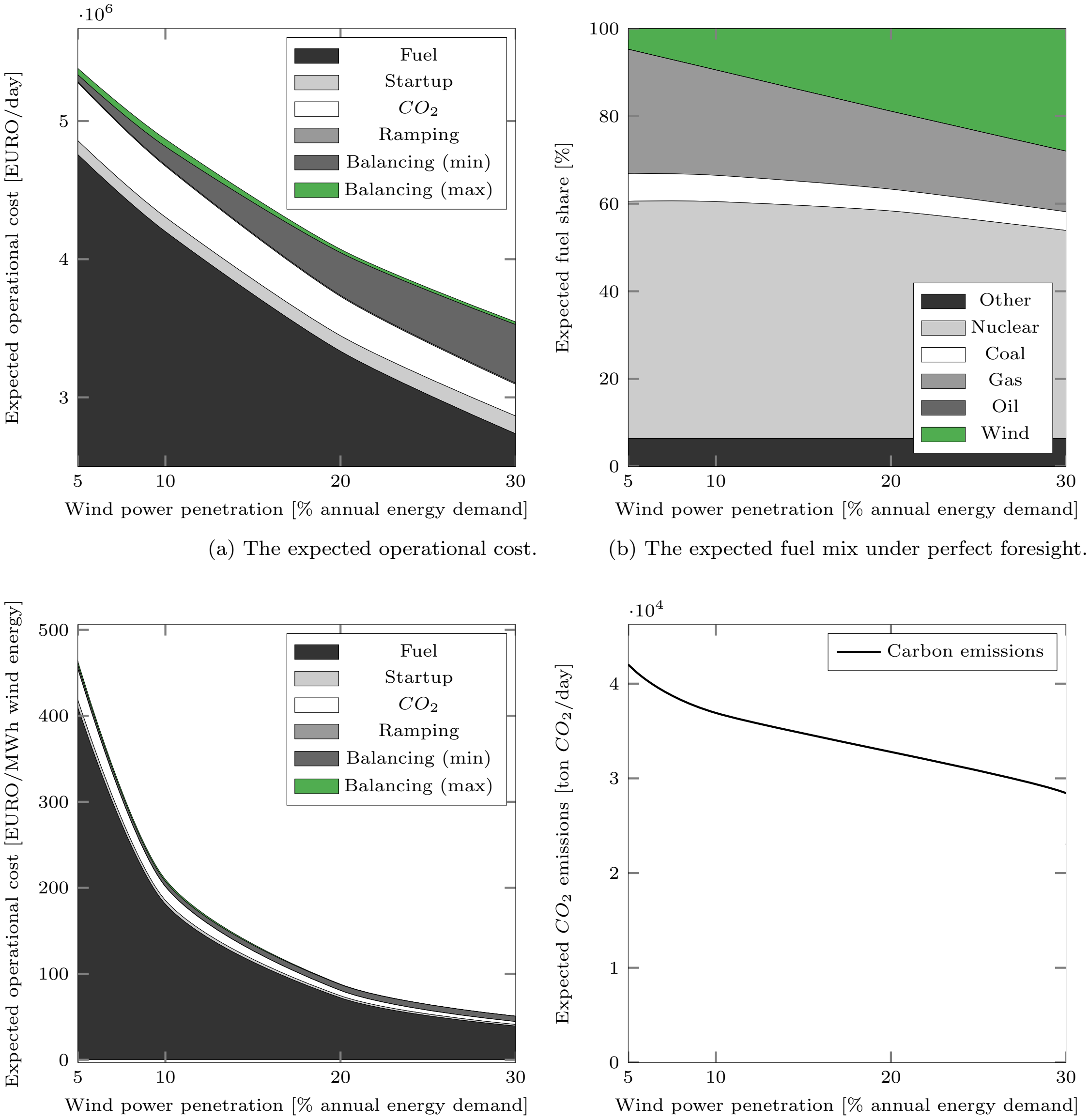
As balancing costs are difficult to interpret without being able to compare them the overall impact of wind power on the system, we will first discuss the latter, based on the results obtained under the *perfect foresight* assumption. Results show that the integration of wind decreases the operational cost of electricity generation. Gas-fired generation is pushed out of the generation mix, which leads to low utilization rates of these units. As a result, they may not be profitable, leading to shut-downs. However, as shown below, these units are needed to maintain the power system balance. Second, the balancing cost is discussed in detail. As shown below, mainly load shedding (due to a decreased reliability) and increased fuel costs lead to a lower limit of these balancing costs in the order of 4.3 to 6.7 Euro per MWh of wind energy. The additional fuel costs are the result of forced partial loading operation to provide upward reserves and increased generation from conventional power plants to compensate for curtailed wind energy. Sub-optimal planning of the needed flexibility can however increase these balancing costs up to 92% (8.3 Euro per MWh wind energy). In terms of carbon emissions, a modest increase of at least 7.4% at a wind power penetration of 30% due to the uncertainty on the wind power forecast is apparent from the results. The general trend of decreasing carbon emissions with increasing wind power penetration however remains. Last, we show that the reliability of the power system can be maintained by employing advanced, stochastic operational planning methods. The numerical results of the simulations can be found in appendix (A).

5.1 The impact of wind power on the power system under *perfect foresight*

If wind power forecasts were perfect, the operational cost of electricity generation would decrease by over 41% (2.2 million Euro per day) by increasing the wind power penetration from 5% to 30% (Fig. 5). This decrease is the result of reduced fuel and carbon costs. Carbon emissions and thus carbon costs decrease faster than fuel costs because of a nuclear baseload capacity. Start-up costs and ramping costs increase by 28%, respectively 16%. As start-up costs and ramping costs combined make up at most 4.3% of the total operational cost, the decrease in fuel and carbon costs results in a net decrease of the operational cost.

Wind energy displaces mainly gas-fired generation in the fuel mix (Fig. 5). As gas-fired generation is relatively expensive, this leads to a strong decrease in fuel costs. Some coal-fired and nuclear power plants are pushed out of the generation mix as well, especially for high penetration rates of wind power. This results in a strong decrease in carbon emissions (Fig. 5) moving from 5% to 10% wind energy, but a declining abatement rate at high wind power penetrations. Overall, emissions decrease from 42,000 to 23,000 tons tons of CO_2 per day. Although uncertainty on the wind power forecasts does influence the fuel mix to some extend, the same trends remain (see below and Appendix A).

The increase in wind power has a significant impact on the utilization of the conventional generation units (Fig. 6). As more wind power is integrated in the power system, conventional units will have less equivalent full load operating hours. The load duration curves of coal-fired generation and nuclear power plants are shifted to the left. Coal-fired units are affected drastically and from relatively low wind power penetration rates. Nuclear units are affected somewhat less, but significant changes in the load duration curve become apparent from wind power penetrations of 20% and higher. Likewise, the gas-fired generation units have less equivalent full-load hours as the wind power penetration increases. At 5% wind energy in the energy mix, 50% of the installed gas-fired capacity is online for more than 50% of the time. If the wind power penetration increases to 30%, this number drops to about 10% of the time. Moreover, during moments of peak demand and low wind power generation, these gas-fired units remain necessary to maintain the short-term balance between demand and supply. The load duration curve of these gas-fired units becomes more and more peaked and shifted to the left, indicating that these units have less and less running hours to recuperate their fixed expenses. Further research will have to investigate whether these units are still profitable under these conditions.

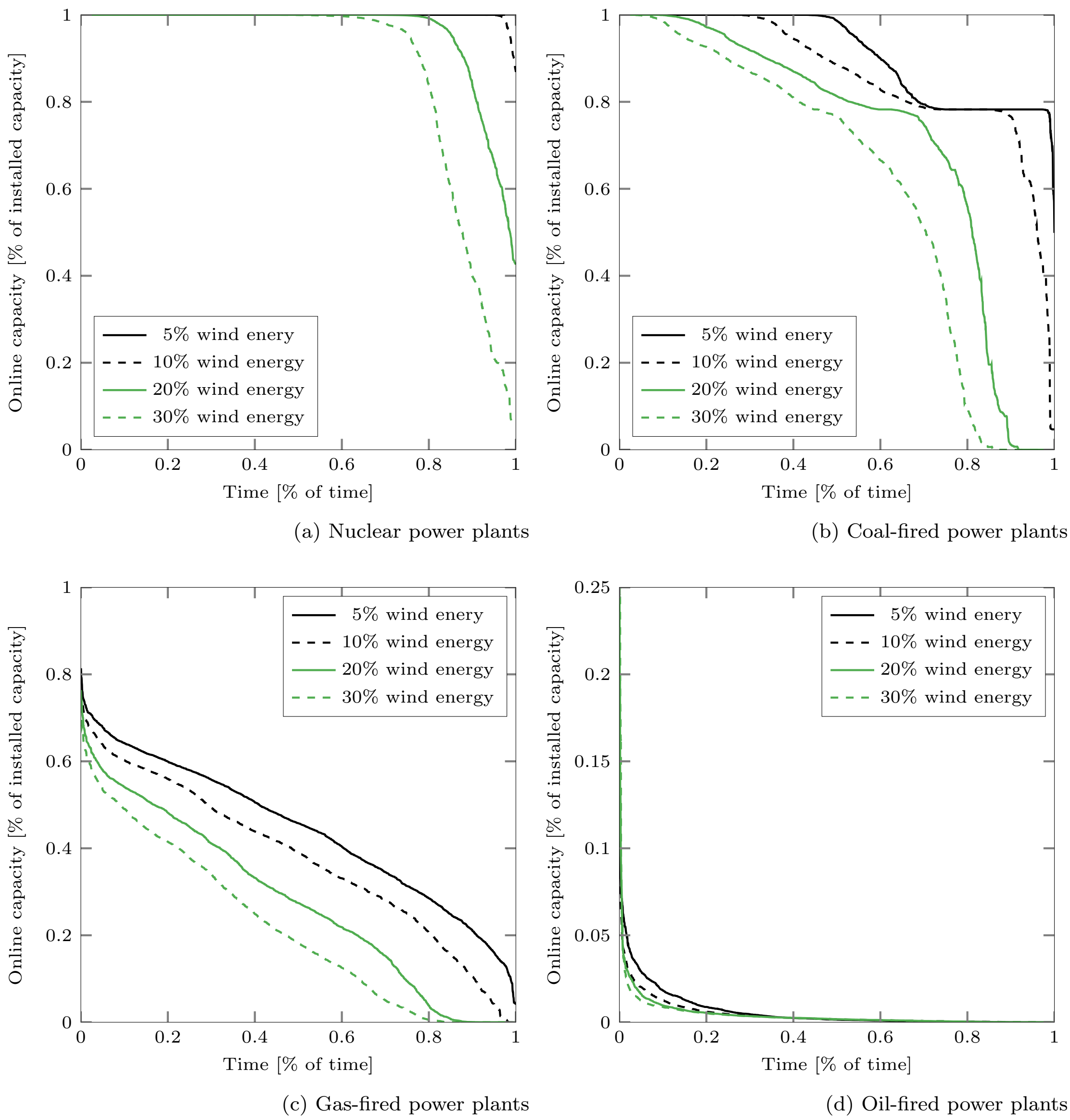


(a) The expected operational cost. (b) The expected fuel mix under perfect foresight.

(c) The expected operational cost. (d) The expected CO_2 emissions under perfect foresight.

Figure 5: The operational cost of electricity generation would decrease by over 41% (2.2 million Euro per day) by increasing the wind power penetration from 5% to 30% if wind power forecasts were perfect. Carbon emissions drop from 42,000 to 23,000 tons tons of CO_2 per day as wind power replaces mainly gas- and coal-fired generation.

Up to this point, all results discussed were obtained from simulations performed under the assumption of perfect foresight. Based on the Monte Carlo evaluation of the stochastic unit commitment and the deterministic unit commitment we have estimated a lower and upper bound for the additional operational balancing costs that appear with the integration of wind power (Fig. 5). Results show that this balancing cost ranges between 50,000 Euro per day (stochastic solution, 5% wind energy) to almost 440,000 Euro per day (deterministic solution, 30% wind energy). This balancing cost rises with the wind power penetration at a nearly linear pace. In relative terms, it makes up 12% of the operational cost at a wind power penetration of 30%. The stochastic solution consistently outperforms the deterministic solution. For example, at a wind penetration of 20%, balancing costs amount to 6.7 Euro per MWh wind energy in the stochastic solution. The deterministic model yields expected balancing costs of approximately 7.2 Euro per MWh wind energy at this wind power penetration – over 8% higher than those of obtained with the stochastic model. The following section, the origin of these balancing costs is discussed in detail.



(a) Nuclear power plants

(b) Coal-fired power plants

(c) Gas-fired power plants

(d) Oil-fired power plants

Figure 6: The load duration curves (obtained under perfect foresight conditions) show a significant decrease of the amount of equivalent full load hours that conventional units are operating with increasing wind power penetrations. Especially gas and coal-fired units are affected. Note that during peak demand, these units are needed to maintain the system balance. Further research will have to show if this number of operating hours is sufficient to recover the fixed costs of these units and thus too remain profitable.

5.2 Balancing costs as a result of imperfect forecasts

Fig. 7 and Table 2 show the the balancing cost on a per MWh of wind energy basis, for the different penetration levels of wind energy and the two models. This balancing cost starts at 4.3 to 8.3 Euro per MWh wind energy at a wind penetration of 5% of the annual energy demand and reaches 6.1 to 6.3 Euro per MWh of wind energy at a wind penetration of 30%. The stochastic model shows the highest balancing cost (6.7 Euro per MWh wind energy) at a wind energy penetration of 20%, while the deterministic model leads to balancing costs up to 8.3 Euro per MWh wind energy at a wind power penetration of 5%.

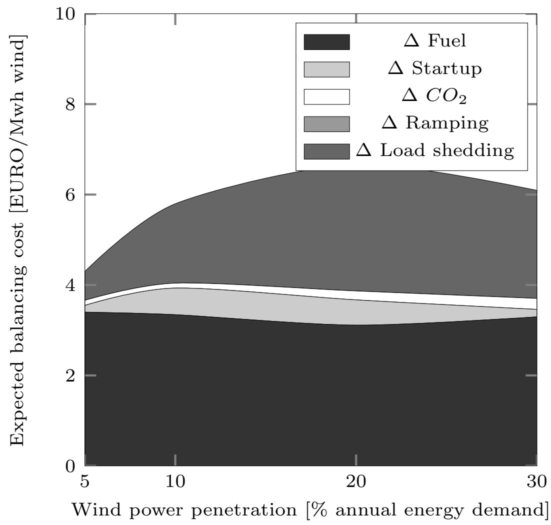
In all cases, an increased fuel cost and a reduced reliability, reflected in a cost related to load shedding, drive the balancing cost. The reason behind this increased fuel cost is twofold. First, the uncertainty on wind power forecast requires the commitment of some reserve capacity, either triggered by the reserve constraints or by the scenarios imposed on the optimization. As a result, more capacity is committed in the unit commitment phase, which means that during the dispatch phase more units will be running in part-load and thus at a lower efficiency. As such, the average fuel cost per MWh increases. Second, this increased capacity leads to a less compressible power system. Power plants cannot operate below their minimum operating point. The sum of the minimum operating points of all online units equals the minimum output of the dispatchable units. If the sum of this number and the available wind power exceeds the demand, this leads to curtailment (Fig. 7). However, this 'lost' energy must be replaced by conventional generation, increasing the average fuel cost. The latter effect only occurs for wind penetrations above 20%. At a penetration of 30%, up to 6% of the available wind energy is curtailed, with little difference between the stochastic and deterministic solution. Start-up costs are increased due to the uncertainty, but no trend can be distilled from the data. Ramping costs are not affected.

Looking at Fig. 7, it is apparent that the lower limit and upper limit on the balancing cost display an opposite trend with increasing wind power penetration. While the lower limit (slightly) increases, the upper limit decreases. The reason for this seemingly contradictory result lies in the linear extrapolation of the reserves inspired by Elia [1] (see above) and the assumption that wind power is the only form of uncertainty in this power system. The reserve calculation as performed by Elia considers all forms of uncertainty in the system and consists of a relatively large 'base' of reserve capacity. Our linear extrapolation of the increase of reserves as a function of the wind power penetration starts from this 'base' capacity of reserves. At low wind power penetration, this leads to large (maximum) reserve capacities compared to the installed wind power capacity. For example, at a 5% wind energy penetration, the maximum reserve capacity is 1.5 GW, which is to be compared to an installed wind capacity of 1.7 GW. Such stringent reserve requirements lead to a high reliability, but at a relatively high balancing cost. At higher wind power penetration rates, the dominance of this 'base' reserve capacity fades. A wind energy penetration of 30% corresponds to a installed wind power capacity of about 10 GW, but the maximum reserve capacity only rises to 3 GW. Although this is a conservative approach, lowering this 'base' of reserve capacity could lead to load shedding, which would lead to unrepresentative results. However, the results above still allow us to illustrate that the superior performance of a stochastic model to deal with uncertainty in terms of operational costs. Moreover, this highlights the importance of adequate and cost-effective reserve requirements in power systems with high RES penetration rates, as these significantly influence the observed balancing costs, even at high reliability levels. Indeed, as illustrated in Table 2, the stochastic model outperforms the deterministic model at every wind power penetration. Balancing costs are up to 92% higher in the deterministic model compared to the stochastic model. This difference decreases to 5% at a wind power penetration of 30%. Note that this difference is however dependent on the cost of load shedding, here arbitrarily set to 10,000 Euro per MWh. If the cost of load shedding is excluded, the stochastic model performs 70% better that the conservative approach.

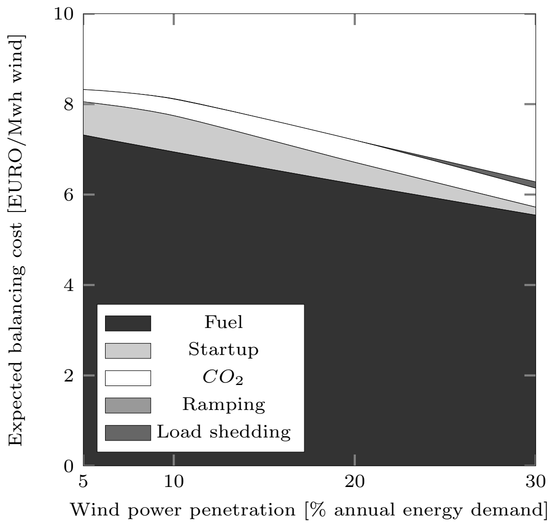
Remarkably, the lower limit of the balancing costs is relatively constant on a per MWh wind energy basis. If the cost of the increased unreliability (load shedding) is excluded, the balancing cost varies between 3.6 and 4 Euro per MWh wind energy, driven by a near-constant additional fuel cost (3.1 to 3.4 Euro per MWh wind energy). This can be explained by looking at the units that provide these balancing services. In effect, the stochastic model chooses gas-fired units to compensate for wind power forecast errors. As these units have similar operational costs, this results in similar balancing costs. This is reflected in the resulting fuel mix (see Appendix A): the unpredictability of wind power shifts some of the generation from coal-fired units to gas-fired units. In the conservative, deterministic model, the shift from coal-fired to gas-fired generation is somewhat more pronounced, as well as a reduction of the share of nuclear power in the energy mix. Balancing fuel costs are not constant in this deterministic solution due to a higher online capacity, leading to more part-load operation of power plants. This effect however does diminish as the share of wind energy increases.

Table 2: The balancing costs mostly consist of additional fuel costs and costs associated with a reduced reliability (load shedding). As the wind penetration increases, the balancing costs increase (lower limit). All costs are expressed in Euro per MWh wind energy.

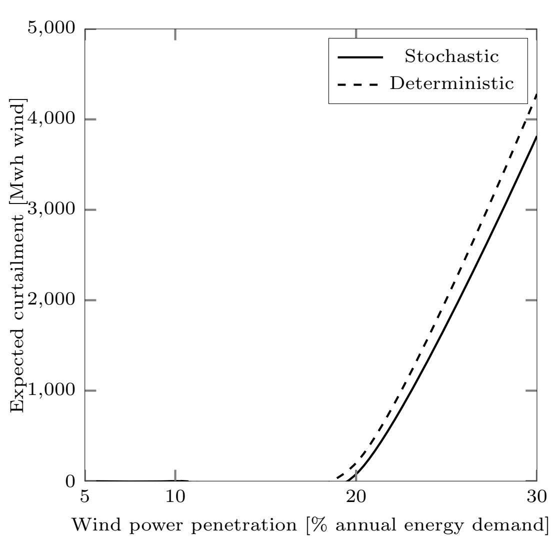
Wind energy	**5%**		**10%**		**20%**		**30%**	
	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
Fuel costs	3.4	7.3	3.3	6.9	3.1	6.2	3.3	5.5
Start-up costs	0.2	0.7	0.6	0.8	0.6	0.5	0.2	0.2
Carbon costs	0.1	0.3	0.1	0.4	0.2	0.5	0.2	0.4
Ramping costs	0	0	0	0	0.2	0	0	0
Load shedding	0.7	0	1.8	0	2.8	0	2.4	0.2
Balancing costs	**4.3**	**8.3**	**5.8**	**8.1**	**6.7**	**7.2**	**6.1**	**6.3**



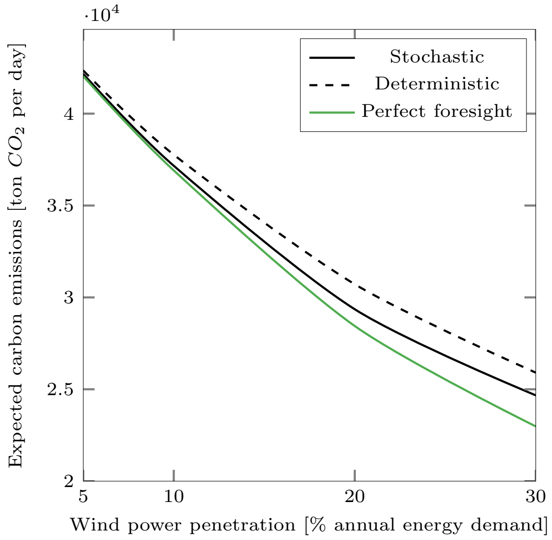
(a) The expected balancing cost (sucm)



(b) The expected balancing cost (ducm)



(c) The expected curtailment



(d) The expected carbon emissions

Figure 7: Balancing costs are driven by increased fuel costs and costs associated with a reduced reliability. The lower limit of the balancing costs is relatively constant as the corresponding balancing services are deliverd by the same units, with similar operational costs. Carbon emissions are significantly increased compared to the perfect foresight-simulations, while curtailment is limited and only occurs at wind power penetrations above 20%.

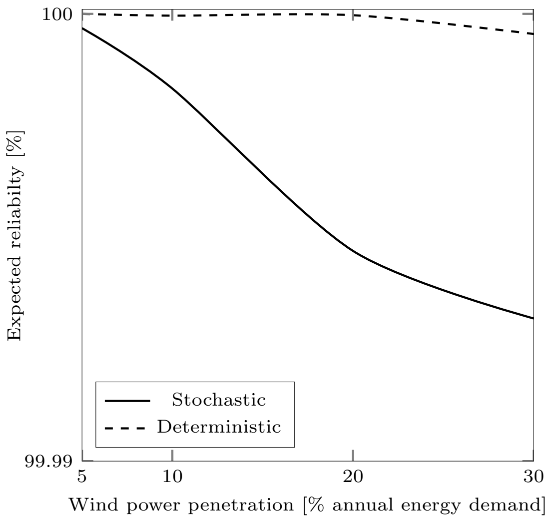


Figure 8: The expected reliability, calculated as 100% - the ratio of the expected load shedding compared to the total load, remains well above 99.99% in both cases.

As a result of the uncertainty and the required spinning reserves to overcome this uncertainty, carbon emissions rise significantly compared to the perfect foresight simulations (Fig. 7). At a 5% wind energy penetration, emissions are 0.3 to 2.3% higher. If the share of wind energy further increases to 30%, carbon emissions are at least 7.4% higher, with a higher bound at 12.7%. Expressed per MWh of wind energy, this corresponds to 0.01 to 0.04 ton CO_2 per MWh wind energy (5% wind energy) or 0.02 to 0.04 ton CO_2 per MWh wind energy (30% wind energy).

5.3 Impact of wind power forecast errors on power system reliability

Last, we discuss the reliability of the resulting unit commitments. We calculate this reliability as the one minus the ratio of the expected load shedding ($E[LL]$) to the total load (DEM):

$$E[REL] = 1 - \frac{E[LL]}{DEM}. \quad (5)$$

As shown in Fig. 8, the expected reliability remains well above 99.99% in both cases. The deterministic solution yields reliability levels above 99.9999% for wind power penetration levels up to 20%. However, as shown above, this comes at a high cost. Although the amount of load shedding is low, it makes up a relatively large share of the balancing cost in the stochastic solution as load shedding is penalized at 10,000 Euro per MWh in the optimization. However, regardless of this cost, the stochastic solution outperforms the deterministic model in terms of expected costs, at the expense of a very limited loss in reliability.

6 Conclusion

With the increase of intermittent generation from renewable energy sources (RES), the discussion on the integration costs associated with these intermittent renewables has become a very active field of research. Due to their location-specific, variable and limitedly predictable character, they affect the power system in terms of generation and grid adequacy, as well as on the need of short term balancing services.

In this paper, we focus on the cost associated with balancing – i.e. maintaining the balance between supply and demand on the short term – resulting from a specific source of uncertainty, namely the error on wind power forecasts (WPFE). We study the impact of this forecast error on the operational power system costs and carbon emissions, expanding the work presented at the 2nd BAEE research workshop (Benelux Association for Energy Economics) [7]. An estimate of the balancing cost from a system perspective for a system inspired on the Belgian power system was obtained via a state-of-the-art stochastic modeling framework. Compared to the current literature, this approach is richer in the detail of the modeling of this uncertainty. It allows us to provide a lower bound on the balancing costs by looking at the stable solution of the resulting stochastic problem.

Results show that the lower bound on balancing costs varies between 4.3 and 6.7 Euro per MWh of wind energy for wind power penetrations between 5% and 30%. These values are in line with values found in the literature. If one excludes the cost of a reduced reliability, the balancing cost becomes relatively constant, ranging from 3.6 to 4 Euro per MWh of wind energy. This is the result of the fact that the same units, with similar operational costs, are used to balance wind power, for these penetration rates. Likewise, carbon emissions are shown to rise up to 7.4 - 12.7% compared to the case where no uncertainty exists on the wind power forecast. Comparison with a deterministic optimization, considering a conservative reserve requirement inspired by Elia [1], the Belgian TSO, reveals that sub-optimal scheduling of reserves can lead to significantly increased balancing costs, up to 8.3 Euro per MWh wind.

The latter result shows that power system operators, utilities and policy makers jointly should strive to

- improve, or give incentives to improve, forecasts on power generation from RES, as balancing costs are non-negligible, even at low wind power penetrations;
- ensure that sufficient capacity is available to provide these balancing services, as wind power pushes the much-needed flexible units out of the fuel mix;
- employ state-of-the-art operational modeling techniques to estimate the required reserves needed to cover the remaining uncertainty, in order to minimize the resulting balancing costs.

This work may be expanded in the following ways. First, the profitability of the dispatchable units under these high wind power penetrations should be investigated. If operators are unable to recover fixed costs, power plants may be decommissioned. Balancing costs and reliability will be affected by such decisions. A solution to this weakness may be to include investments and disinvestments in the model. Second, the inclusion of uncertainty during the dispatch and the adaptation of the unit commitment during the dispatch (e.g. starting of peaking units) is currently not included. This would further increase the realism of the model, as in reality information becomes available as time progresses. The impact of such measures on the balancing costs should be investigated. In addition, multiple sources of uncertainty could be integrated in the model. Third, the obtained balancing costs should be compared to and validated against market data, such as imbalance volumes and prices, as well as (activated) reserve volumes.

Acknowledgment

The computational resources and services used in this work were provided by the Hercules Foundation and the Flemish Government – department EWI.

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A Simulation results

Table 3 summarizes the numerical results obtained from the simulations:

- the expected operational costs, split up in fuel, start-up, carbon, ramping and load shedding costs;
- the expected curtailment, carbon emissions and load shedding;
- the share of the various fuels in the generation mix;
- the average demand for electrical energy.

Table 3: Numerical results of the simulations. 'PF' stands for perfect foresight, 'STOCH' for stochastic and 'DET' for deterministic.

(a) 5 and 10% wind power penetration

Wind penetration			**5%**			**10%**	
		PF	**STOCH**	**DET**	**PF**	**STOCH**	**DET**
Expected operational cost	EUR	5285486	5335401	5381736	4680840	4815396	4869352
Fuel costs	EUR	4757809	4797260	4842745	4199935	4277539	4361112
Start-up costs	EUR	100381	102124	108888	104525	118196	123136
Carbon costs	EUR	420340	421641	423502	369105	371631	377661
Ramping costs	EUR	6955	6560	6514	7275	6929	6554
Load shedding	EUR	0	7816	87	0	41101	888
Curtailment	MWh	0.00	0.00	0.00	0.00	0.00	0.00
Carbon emissions	tCO2	42034	42164	42350	36910	37163	37766
Load shedding	MWh	0.00	0.78	0.01	0.00	4.11	0.09
Rest	%	6.4	6.4	6.4	6.4	6.4	6.4
Nuclear	%	54.2	54.2	54.2	54.1	54.1	53.8
Coal	%	6.3	6.2	6.1	6.0	5.8	5.7
Gas	%	28.4	28.5	28.6	24.1	24.4	24.7
Oil	%	0.0	0.0	0.0	0.0	0.0	0.0
Wind	%	4.7	4.7	4.7	9.4	9.4	9.4
Demand	MWh	245725	245725	245725	245725	245725	245725

(b) 20 and 30% wind power penetration

Wind penetration			**20%**			**30%**	
		PF	**STOCH**	**DET**	**PF**	**STOCH**	**DET**
Expected operational cost	EUR	3737841	4047260	4072224	3102611	3520451	3540058
Fuel costs	EUR	3333674	3478139	3622847	2736419	2962571	3122502
Start-up costs	EUR	112215	138193	134741	128368	137139	140744
Carbon costs	EUR	284426	293553	307171	229798	246309	259066
Ramping costs	EUR	7526	7063	6649	8026	7090	6579
Load shedding	EUR	0	130312	816	0	167342	11166
Curtailment	MWh	0.00	76.71	201.34	0.00	3817.00	4281.18
Carbon emissions	tCO2	28443	29355	30717	22980	24631	25907
Load shedding	MWh	0.00	13.03	0.08	0.00	16.73	1.12
Rest	%	6.4	6.4	6.4	6.4	6.4	6.4
Nuclear	%	52.0	51.6	50.9	47.5	47.8	47.2
Coal	%	5.0	4.8	4.8	4.3	4.1	4.0
Gas	%	17.8	18.4	19.1	13.8	14.9	15.7
Oil	%	0.0	0.0	0.0	0.0	0.0	0.0
Wind	%	18.9	18.9	18.9	28.3	28.3	28.3
Demand	MWh	245725	245725	245725	245725	245725	245725